Ministry of Science and Technology – Advanced Intelligent Automation Technology Project

Intelligent Manufacturing Cloud (IMC)

-Intelligent Cloud Computing Services Platform for Machine Tool Industry-

IMC Demo

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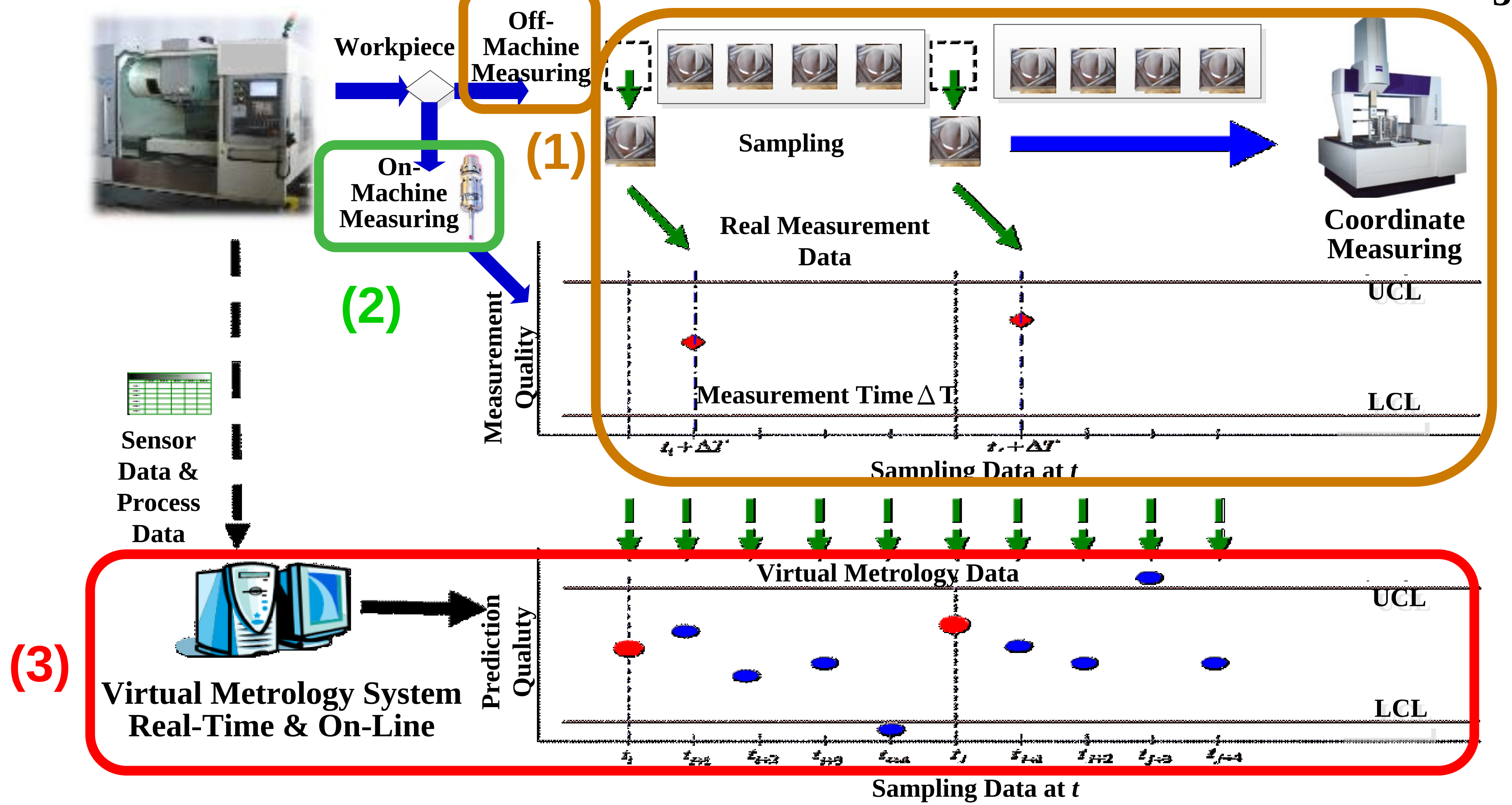
Premise

- **Automatic Virtual Metrology (AVM) can convert off-line sampling inspection with metrology delay into real-time and on-line total inspection. It has been successfully applied to the semiconductor, TFT-LCD, and solar cell industries.**

- **AVM has been granted R.O.C., U.S.A., Japan, China, and Korea patents. Moreover, it has won the 2012 National Invention and Creation Award (Gold Medal) from MOEA, R.O.C.**

- **This project aims at leveraging several technologies, including AVM, to develop an intelligent manufacturing cloud (IMC) for providing various intelligent value-added manufacturing services for machine tools.**

Virtual Metrology (VM) vs. Traditional Measurements



- **VM can convert** <u>**sampling inspections with metrology delay**</u> **into** <u>**real-time and on-line total inspection**</u>.

AVM Application Example
Max-Distance Prediction of Cellphone's Camera Hole

- The tolerance of max-distance is 20 mm ± 15 um.
- Ignoring the errors of 29th testing sample, the maximal errors of the BPNN and PLS models are 5.3 um and 7.6 um, respectively, and the MAEs of the BPNN and PLS models are 2.4 um and 2.5 um, respectively.
- The reason is that occurrence of abnormal process data was detected due to the GSI value of 29th testing sample being higher than the threshold as shown in Fig. A; meanwhile, the actual measurement data (19.968 mm) is out of lower control limit (19.985 mm).
  - **Early warning is sent accordingly – one of merits of TOTAL INSPECTION.**

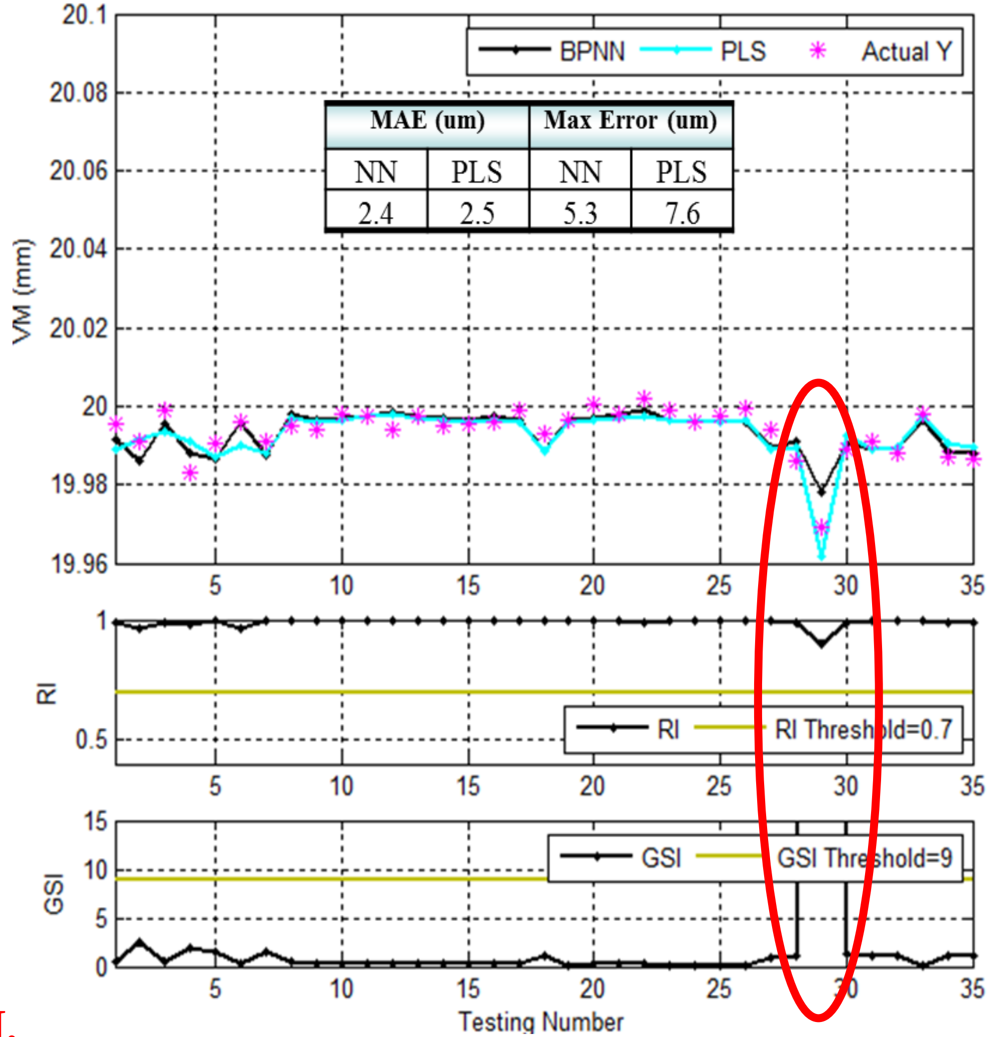
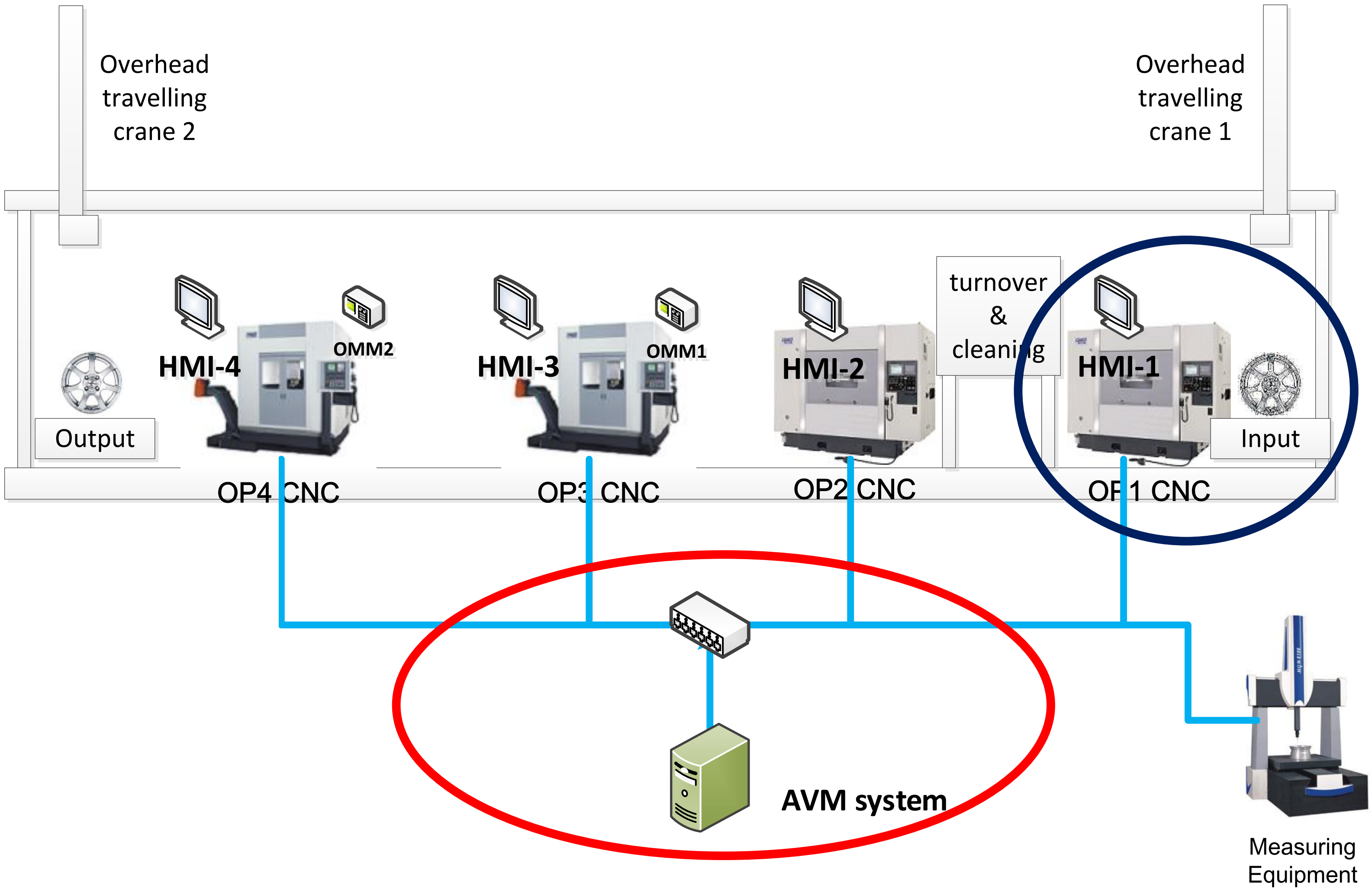


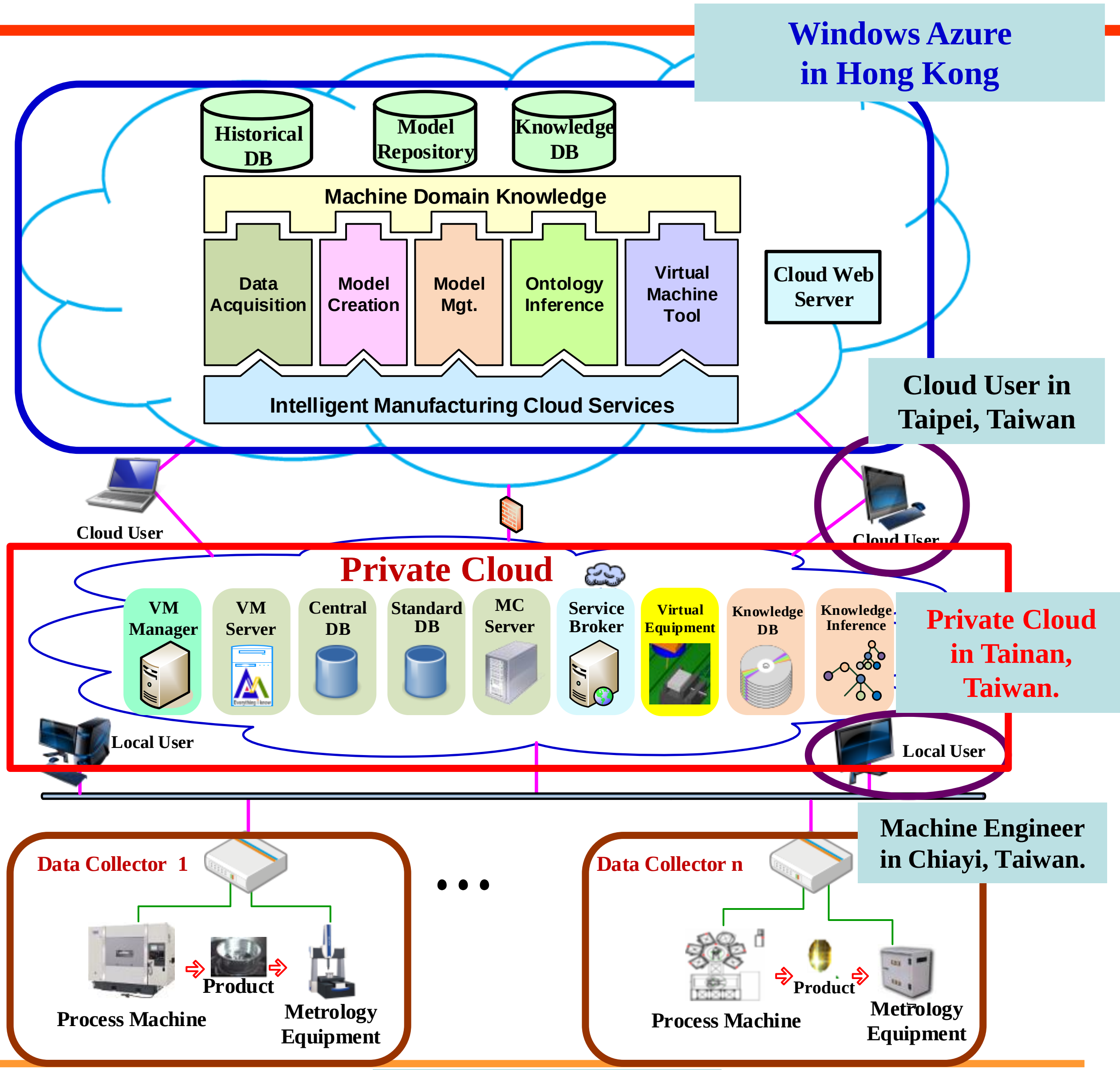
Fig. B. VM_I of Max-Distance of Cellphone's Camera Hole.

Integrating AVM into Wheel Machining Automation – Automated Production Line 1



OP1 Demo

IMC Architecture



Factory Automation Technology, Chiayi, Taiwan.

Demo Scenarios

- **Scenario 1：** **Use Virtual Machine Tool to Simulate Toolpath and Collision Detection**
  (Present by Professor R.-S. Lee and Professor Y.-C. Kao)

- **Scenario 2：** **Apply Computer Aided Process Planning Service to Wheel Factory in Public Cloud**
  (Present by Professor C.-C. Chen)

- **Scenario 3：** **Create Prediction Model in Private Cloud**
  (Present by Professor M.-H. Hung)

- **Scenario 4：** **Conduct Product Precision Prediction (PPP) for Wheel Machining in Private Cloud**
  (Present by Professor H.-C. Yang)

Scenario 1:

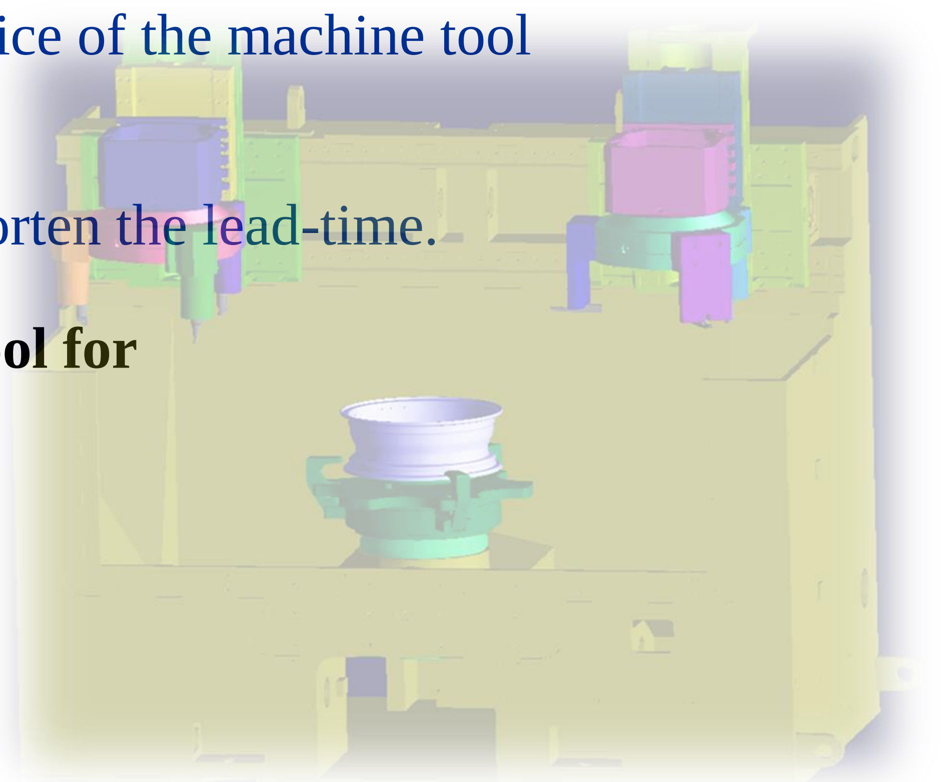
Use Virtual Machine Tool (VMT) to Simulate Toolpath and Collision Detection

After finishing the process planning, a manufacturing engineer uses VMT to simulate and evaluate the machining process.

Pro. R.S. Lee & Pro. Y.C. Kao

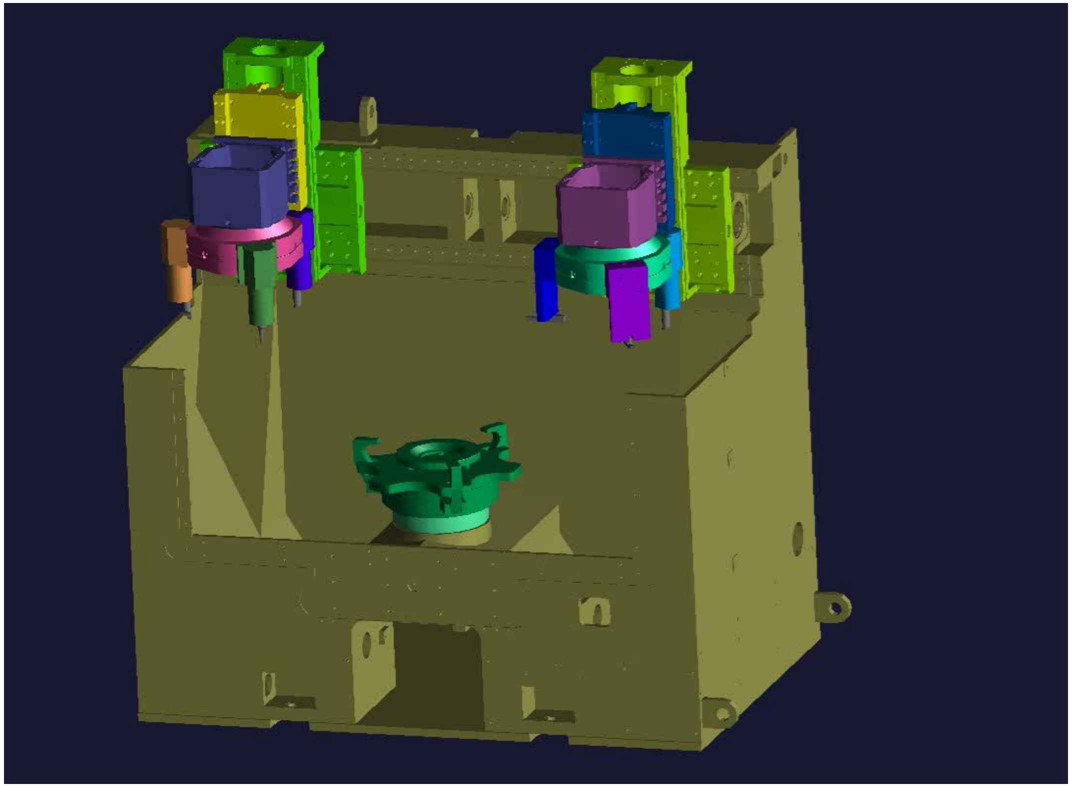
Scenario 1: Use VMT to Simulate Toolpath and Collision Detection

- **What is virtual machine tool?**
  - 3D solid model, topology structure, virtual controller
- **Why do we need virtual machine tool?**
  - It costs **10%~20%** of the price of the machine tool when machine tool collides.
  - Evaluate the process and shorten the lead-time.
- **We can use virtual machine tool for**
  - Motion simulation
  - Check toolpath
  - Collision detection



Scenario 1: Use VMT to Simulate Toolpath and Collision Detection

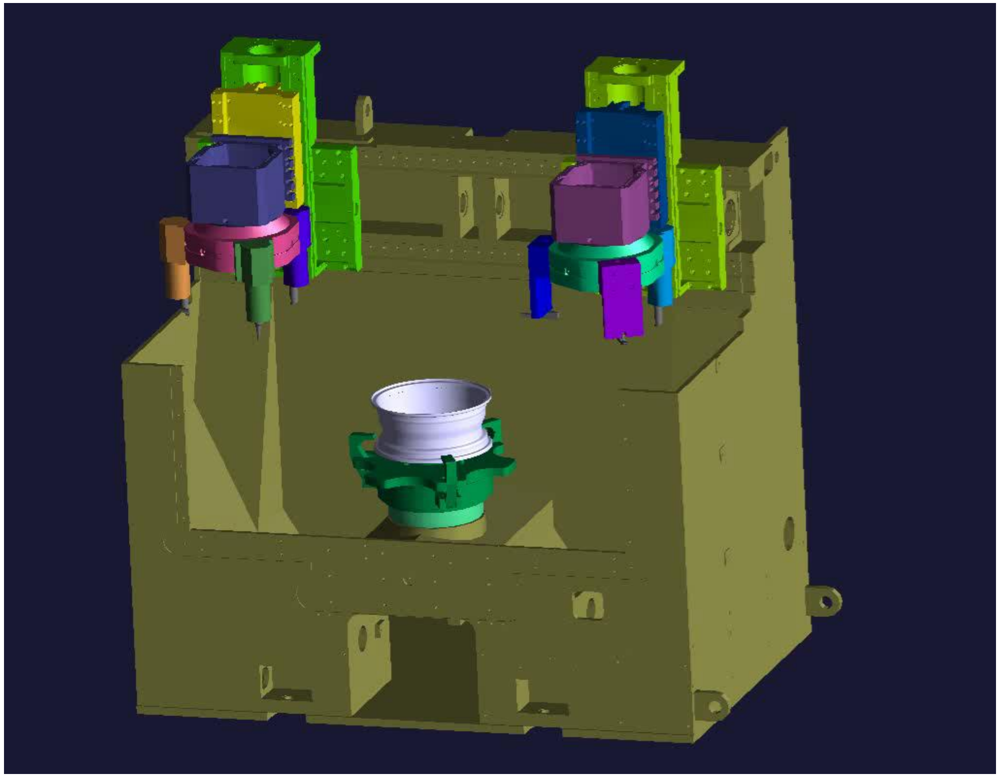
Motion simulation and toolpath display



To simulate motion of the machine for evaluating the tool path of the process.

Scenario 1: Use VMT to Simulate Toolpath and Collision Detection

Collision Detection



To check that whether the machine is collided, including all component of the machine tool.

Scenario 2:

Apply Computer Aided Process Planning (CAPP) Service in Public Cloud to Facilitate Wheel Manufacturing

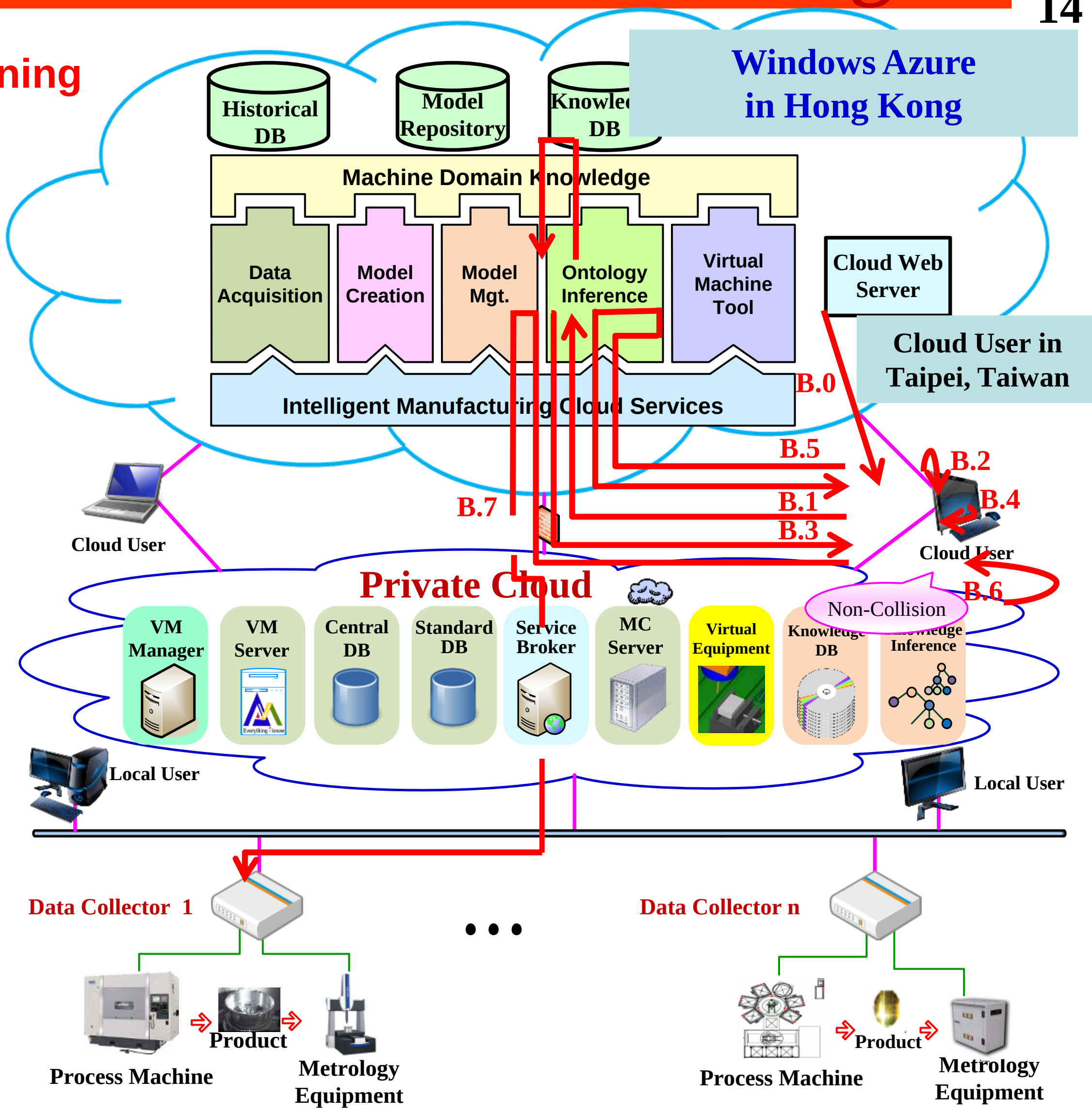
An engineer uses the CAPP service hosted in the public cloud to select collision-free cutting tools for wheel manufacturing.

Present by Professor C.-C. Chen

Scenario 2 : Apply CAPP Service in Public Cloud to Facilitate Wheel Manufacturing

CAPP: Computer Aided Process Planning

B.0: Download the GUI of CAPP Service and login.
B.1: Retrieve cutting tool ontology.
B.2: Input parameters & rules.
B.3: Infer suitable cutting tools.
B.4: Select alternative cutting tools.
B.5: Perform the collision detection and calculate processing time.
B.6: If any collision exists, select other cutting tool and repeat steps B.4 and B.5.
B.7: Send the workpiece files to the process machine through the Service Broker.



Demo of Scenario 2

Apply Computer Aided Process Planning (CAPP) Service in Public Cloud to Facilitate Wheel Manufacturing

Scenario 3:
Create Prediction Model in Private Cloud

An engineer creates a set of prediction models by using the model creation service hosted in the private cloud.

Present by Professor M.-H. Hung

Scenario 3 : Create Prediction Model in Private Cloud

C.0: Download Model Creation GUI and login.

C.1: Retrieve historical indicator & metrology data from Standard DB.

C.2: Create Models

(consisting of several steps)

(1) Data Collection,

(2) Group Setting,

(3) Expert Knowledge,

(4) Indicator Exclusion,

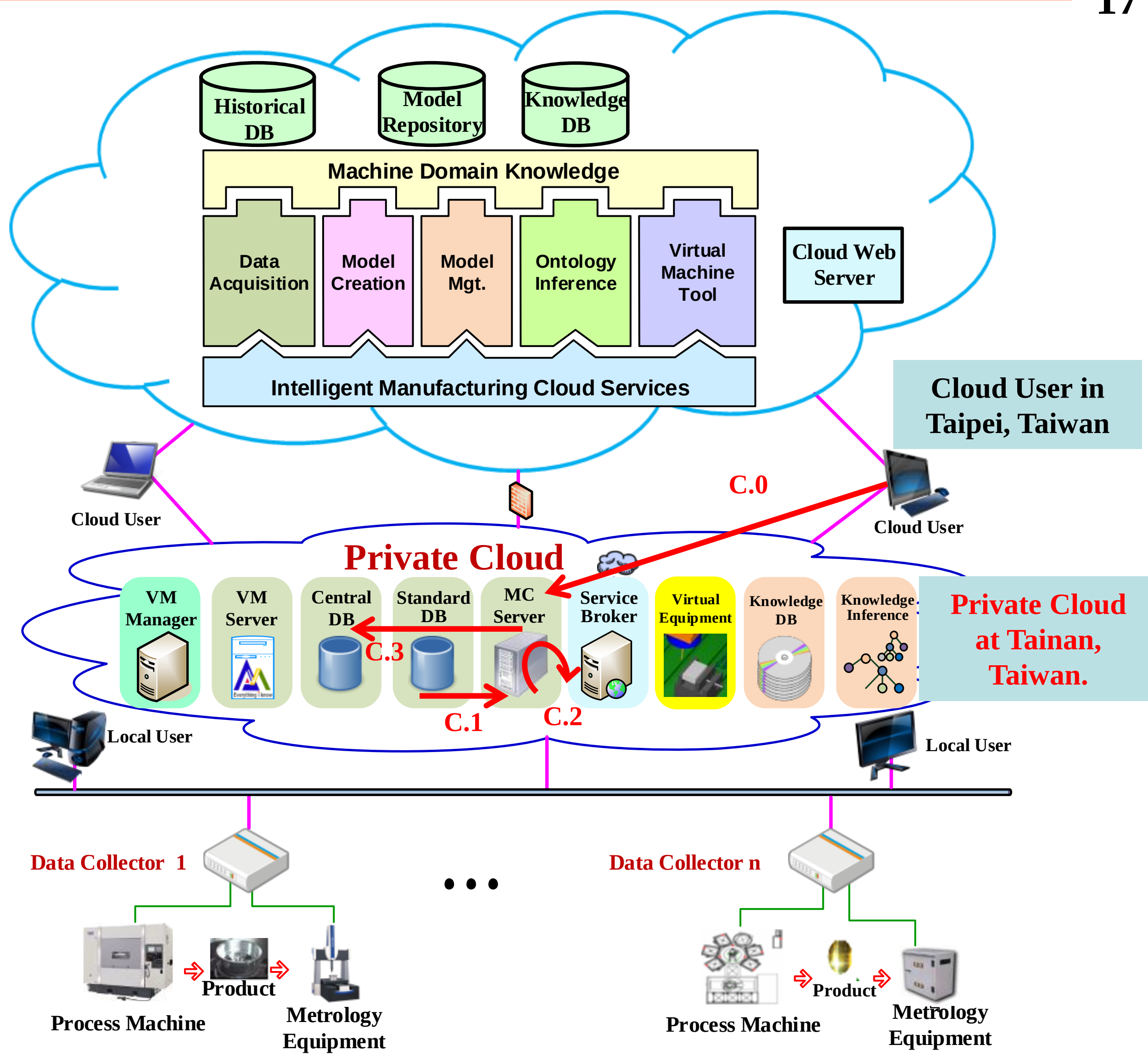
(5) Metrology Exclusion,

(6) DQI_X Verification,

(7) DQI_y Verification,

(8) Prediction Model Creation.

C.3: Store the created models to Central DB.



Demo of Scenario 3

Create Prediction Model in Private Cloud

Scenario 4:

Conduct Product Precision Prediction (PPP) for Wheel Machining in Private Cloud

An engineer operates VM GUI to conduct PPP for wheel machining

Present by Professor H.-C. Yang

Scenario 4 : Conduct PPP for Wheel Machining in Private Cloud

PPP: Product Precision Prediction

D.0: Download VM GUI and login.

D.1: a) Collect Sensory data and process parameters;

b) Derive features from collected data;

c) Store the features into Standard DB.

D.2: Notify VM Manager to conduct a new PPP service.

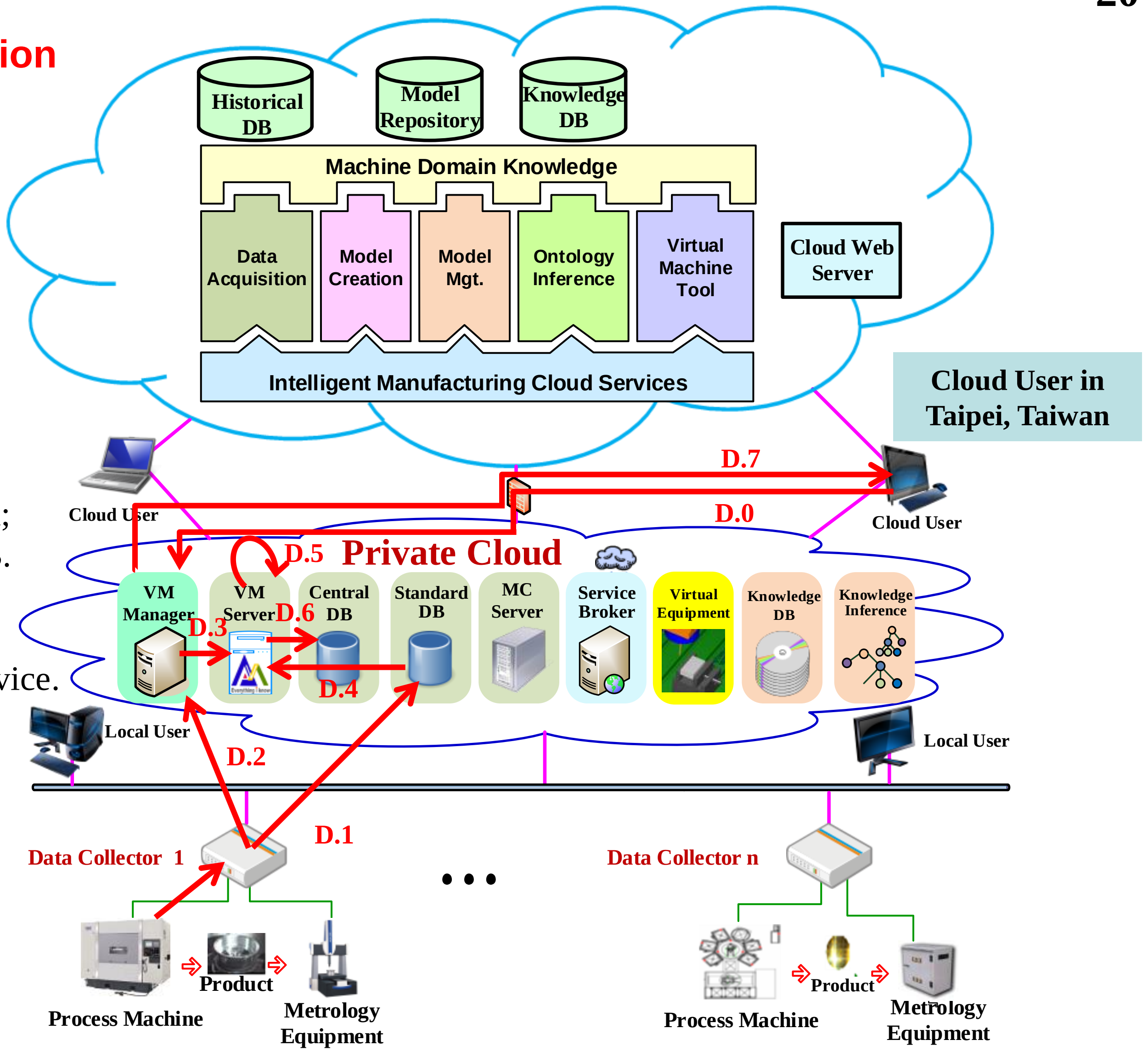
D.3: Inform VM Server to start the PPP service.

D.4: Retrieve features from STDB.

D.5: Compute VM values.

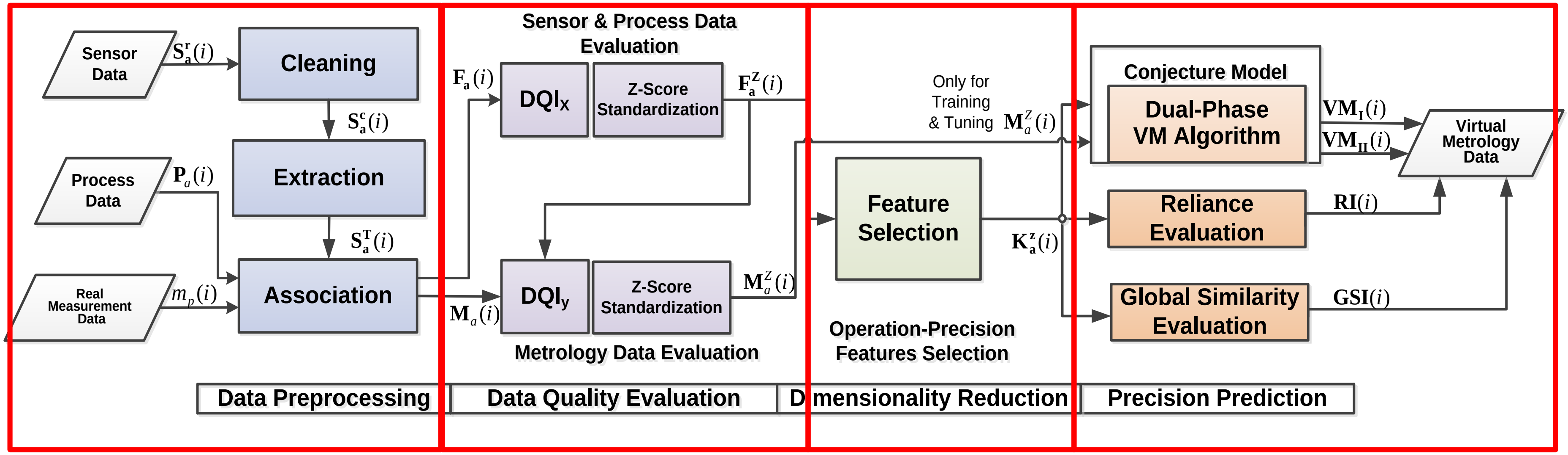
D.6: Store VM values into Central DB.

D.7: Display VM values on GUI.



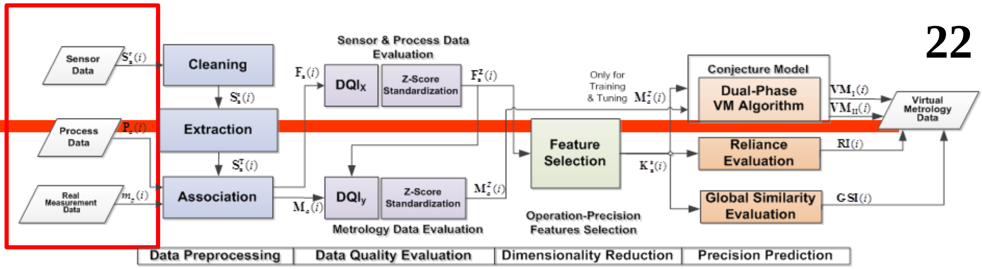
Functions of AVM Server

- Data Acquisition and Data Preprocessing
- Data Quality Evaluation
- Dimensionality Reduction
- Precision Prediction



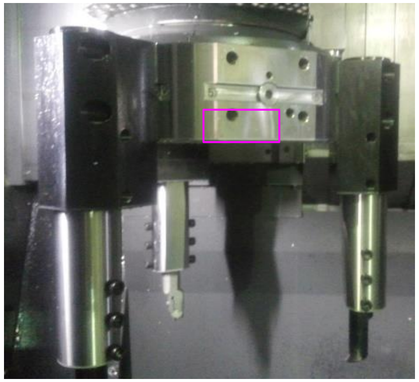
- H. Tieng, H.-C. Yang, M.-H. Hung, and F.-T. Cheng, "A Novel Virtual Metrology Scheme for Predicting Machining Precision of Machine Tools," in *Proc. of The 2013 IEEE International Conference on Robotics and Automation (ICRA 2013)*, Karlsruhe, Germany, pp. 264-269, May 6-10, 2013. **[Best Automation Paper Award]** (NSC 100-2622-E-327-015-CC3, NSC 100-2221-E-034-020, Project AIM-HI of MOE, ROC)

Data Acquisition

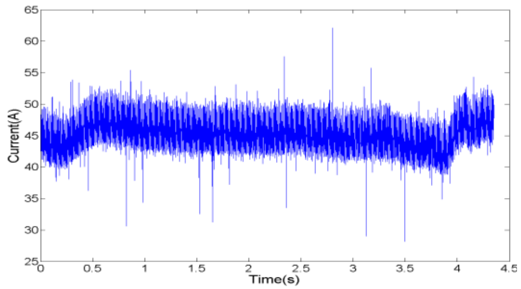


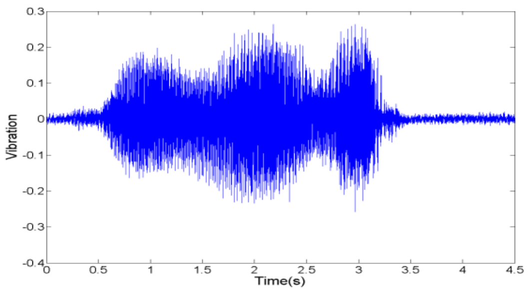
- **Process Parameters**
  - Feed Rate, Spindle Speed and Cutting Depth

- **Sensory Data**
  - Accelerometer
  - Current Sensors



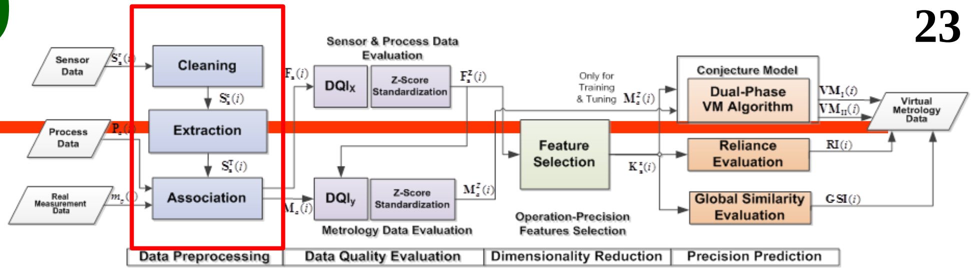
- **Real Metrology Data**
  - Flatness
  - Central Hole Size
  - Outer Diameter Size



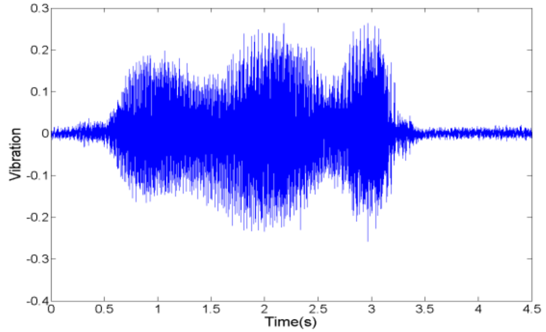


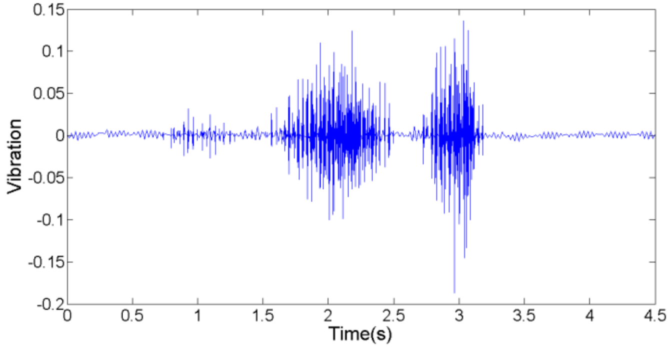
Data Preprocessing (1/3)

Data Cleaning

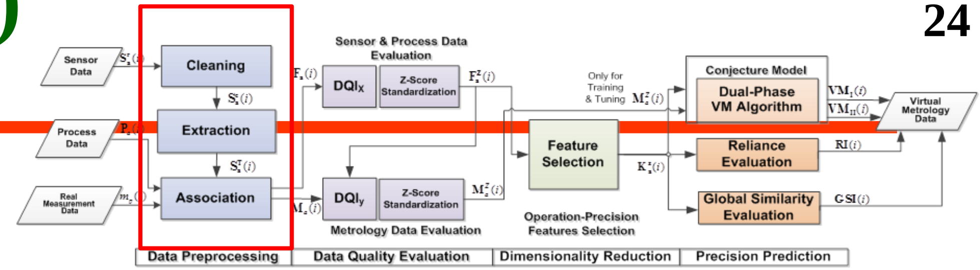


- Data Cleaning has to be performed for data quality assurance.
  - Non-stationary signals, e.g., edge, peak, break, and noise.
  - Wavelet-based thresholding de-noising method.

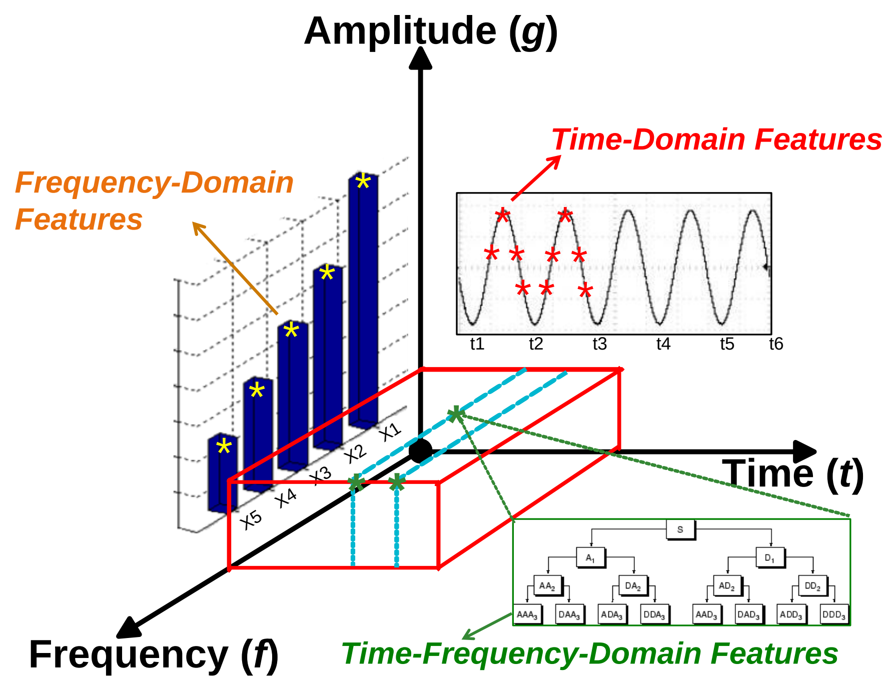




Data Preprocessing (2/3)
Feature Extraction

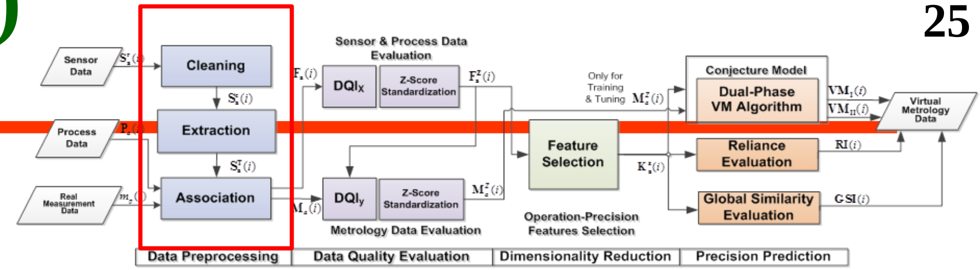


- Three domains from which the features of sensor data are extracted:
  - **Time Domain**
    - RMS, Average, Peak to peak, Kurtosis, Skewness, Variance.
  - **Frequency Domain**
    - Discrete Fourier Transform
  - **Time-Frequency Domain**
    - Wavelet Package Transform

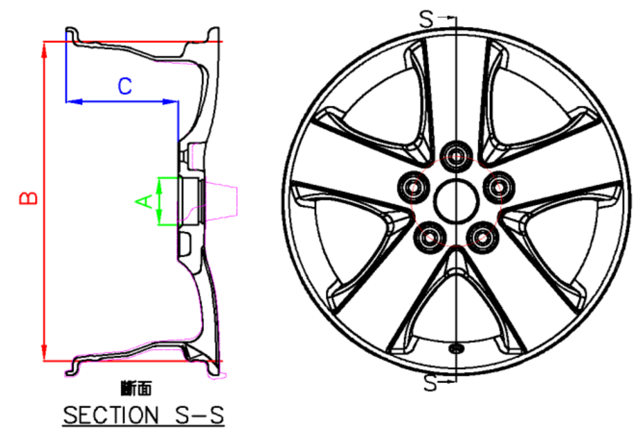


Data Preprocessing (3/3)

Association

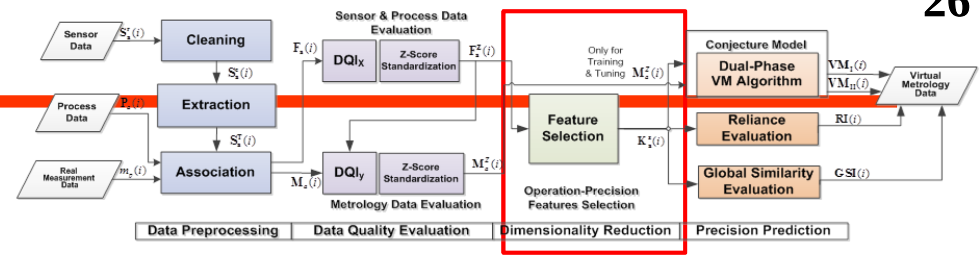


- Association refers to building the mapping relations of a measurement item and the corresponding machining operations.
  - three machining operations identified by A, B, and C.
  - measurement items: flatness, central hole size, and outer diameter size.
  - Association: Embed M codes into NC codes to associate operations with measurement items.

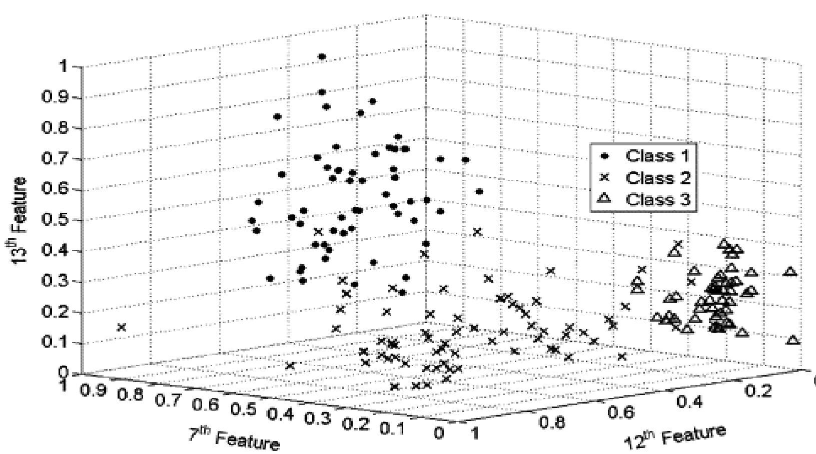


Dimensionality Reduction

Feature Selection



- **Feature Selection** refers to selecting key features from the original feature set.
- The NSGA-II method is used to automatically search key machining features for reducing the dimensionality of the features.



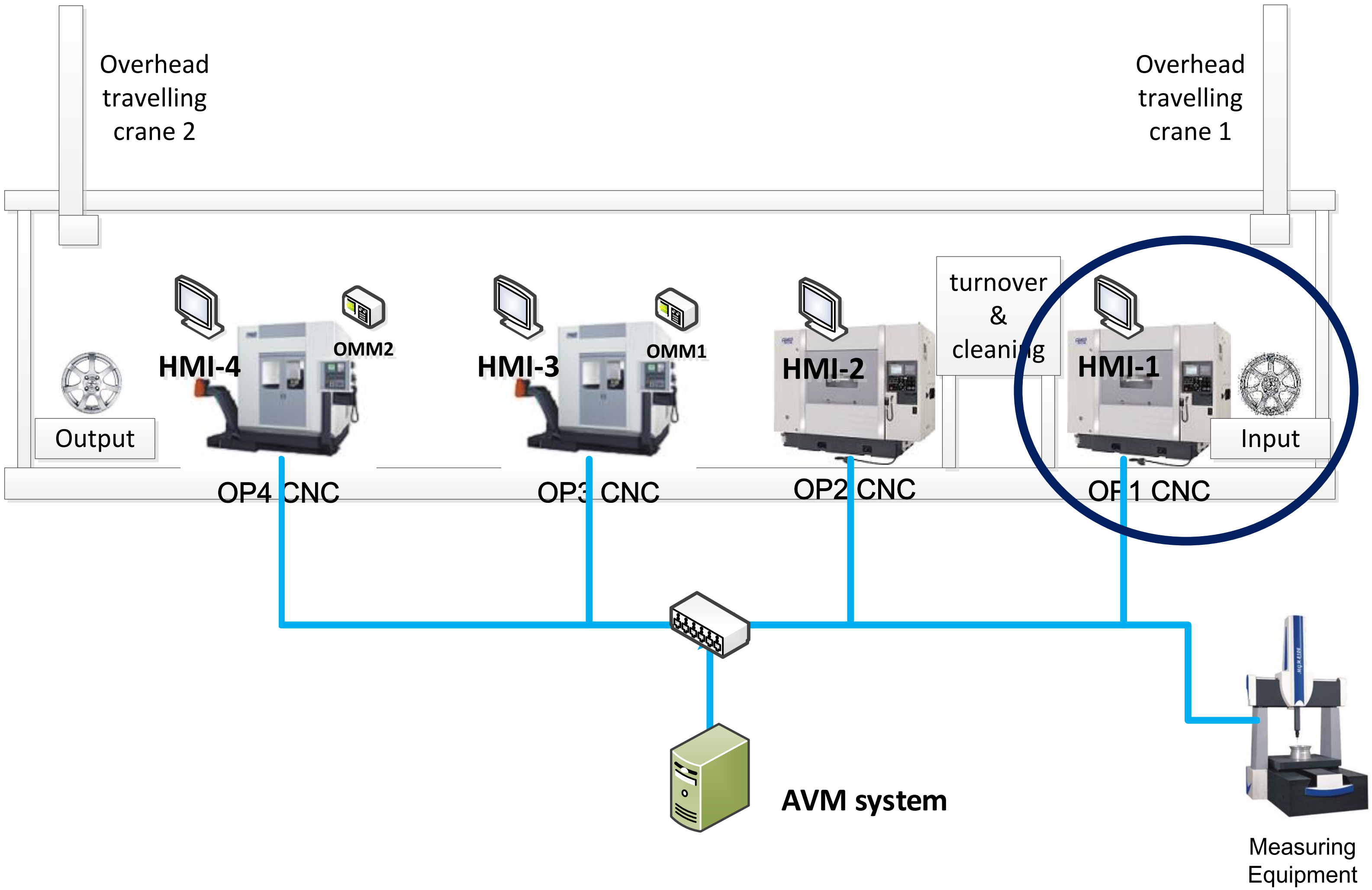
Key Feature Selection of Flatness by NSGA-II

Signal Type	Sensor Location	Op1, Step 2							
		ID	Indicator Name	ID	Indicator Name	ID	Indicator Name	ID	Indicator Name
Vibration	Left Turret(#2) - Tool	1	Frequency Band x1/4	8	Kurtosis (ku)	15	Wavelet Package Node 1	22	Wavelet Package Node 8
		2	Frequency Band x1/2	9	Crest Factor	16	Wavelet Package Node 2	23	Wavelet Package Node 9
		3	Frequency Band x1	10	Root Mean Square	17	Wavelet Package Node 3	24	Wavelet Package Node 10
		4	Frequency Band x2	11	Mean (μ)	18	Wavelet Package Node 4	25	Wavelet Package Node 11
		5	Frequency Band x3	12	Max	19	Wavelet Package Node 5		
		6	Standard Deviation(σ)	13	Min	20	Wavelet Package Node 6		
		7	Skewness	14	Peak to Peak	21	Wavelet Package Node 7		
Current	Spindle Main Motor	26	Frequency Band x1/4	33	Kurtosis (ku)	40	Wavelet Package Node 1	47	Wavelet Package Node 8
		27	Frequency Band x1/2	34	Crest Factor	41	Wavelet Package Node 2	48	Wavelet Package Node 9
		28	Frequency Band x1	35	Root Mean Square	42	Wavelet Package Node 3	49	Wavelet Package Node 10
		29	Frequency Band x2	36	Mean (μ)	43	Wavelet Package Node 4	50	Wavelet Package Node 11
		30	Frequency Band x3	37	Max	44	Wavelet Package Node 5		
		31	Standard Deviation(σ)	38	Min	45	Wavelet Package Node 6		
		32	Skewness	39	Peak to Peak	46	Wavelet Package Node 7		
	Left Turret(#2) - Servo Motor (X axis)	51	Frequency Band x1/4	58	Kurtosis (ku)	65	Wavelet Package Node 1	72	Wavelet Package Node 8
		52	Frequency Band x1/2	59	Crest Factor	66	Wavelet Package Node 2	73	Wavelet Package Node 9
		53	Frequency Band x1	60	Root Mean Square	67	Wavelet Package Node 3	74	Wavelet Package Node 10
		54	Frequency Band x2	61	Mean (μ)	68	Wavelet Package Node 4	75	Wavelet Package Node 11
		55	Frequency Band x3	62	Max	69	Wavelet Package Node 5		
		56	Standard Deviation(σ)	63	Min	70	Wavelet Package Node 6		
		57	Skewness	64	Peak to Peak	71	Wavelet Package Node 7		
	Left Turret(#2) - Servo Motor (Z- axis)	76	Frequency Band x1/4	83	Kurtosis (ku)	90	Wavelet Package Node 1	97	Wavelet Package Node 8
		77	Frequency Band x1/2	84	Crest Factor	91	Wavelet Package Node 2	98	Wavelet Package Node 9
		78	Frequency Band x1	85	Root Mean Square	92	Wavelet Package Node 3	99	Wavelet Package Node 10
		79	Frequency Band x2	86	Mean (μ)	93	Wavelet Package Node 4	100	Wavelet Package Node 11
		80	Frequency Band x3	87	Max	94	Wavelet Package Node 5		
		81	Standard Deviation(σ)	88	Min	95	Wavelet Package Node 6		
		82	Skewness	89	Peak to Peak	96	Wavelet Package Node 7		
Process data	Controller	101	Revolution per Minute	102	Feed Rate				

Demo of Scenario 4

Conduct Product Precision Prediction (PPP) for Wheel Machining in Private Cloud

Integrating AVM into Wheel Machining Automation – Automated Production Line 1



Prediction of Outer Diameter Size

Stage I	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	1.57	6.55	0.0120	0.0498
PLS	3.33	10.59	0.0253	0.0805

Phase I	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	4.48	7.73	0.0340	0.0588
PLS	4.70	11.26	0.0357	0.0932

$$\#MAPE = \frac{1}{N}\sum_{n=1}^{N}\frac{(|Ypre_n - Yreal_n|)}{tolerance}$$

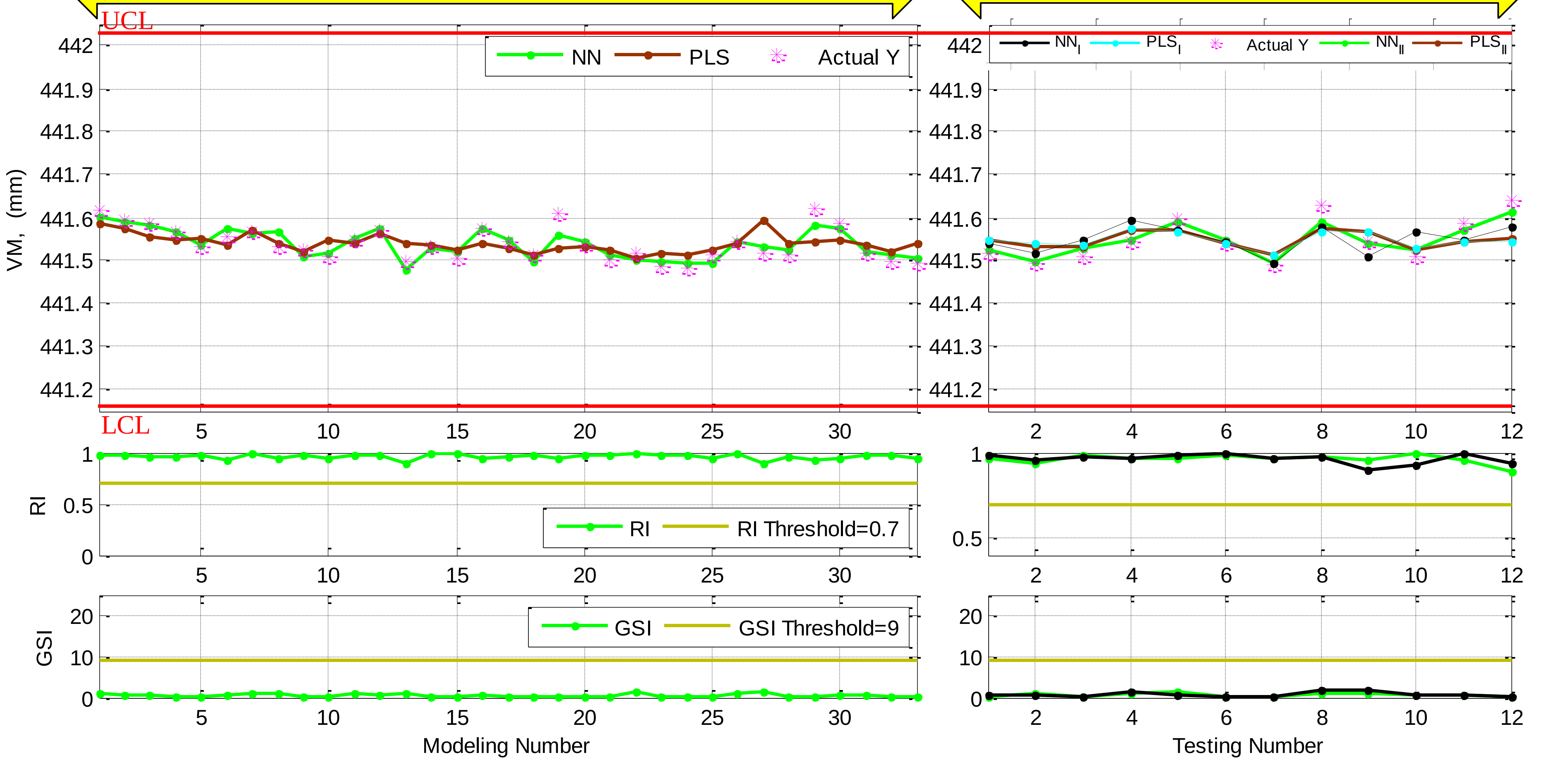
$$\#MAE = \frac{1}{N}\sum_{n=1}^{N}(|Ypre_n - Yreal_n|)$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|),\ n{=}1\ldots N$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|/tolerance),\ n{=}1\ldots N$$

Modeling Samples

Testing Samples



Prediction of Flatness

Stage II	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	3.22	14.48	0.0016	0.0072
PLS	5.98	19.42	0.0030	0.0097

Phase I	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	5.42	11.62	0.0027	0.0058
PLS	7.04	11.50	0.0035	0.0072

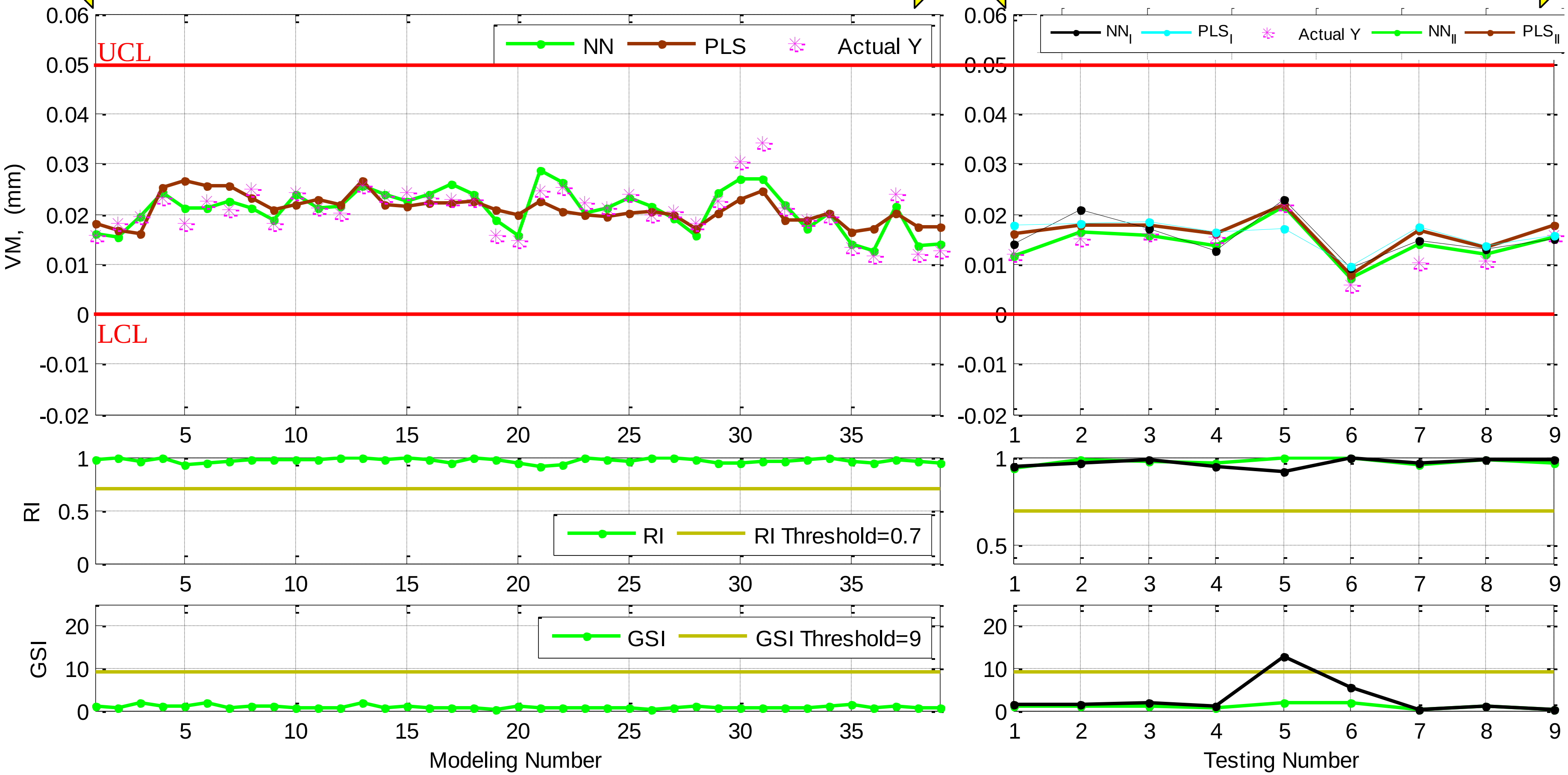
$$\#MAPE = \frac{1}{N}\sum_{n=1}^{N}\frac{(|Ypre_n - Yreal_n|)}{tolerance}$$

$$\#MAE = \frac{1}{N}\sum_{n=1}^{N}(|Ypre_n - Yreal_n|)$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|),\ n=1\ldots N$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|/tolerance),\ n=1\ldots N$$

Modeling Samples **Testing Samples**



Prediction of Central Hole Size

Stage II	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	3.35	12.92	0.0030	0.0116
PLS	2.97	12.23	0.0027	0.0110

Phase I	MAPE(%)	Max Error (%)	MAE(mm)	Max Error(mm)
NN	10.64	30.86	0.0096	0.0278
PLS	9.04	31.64	0.0081	0.0285

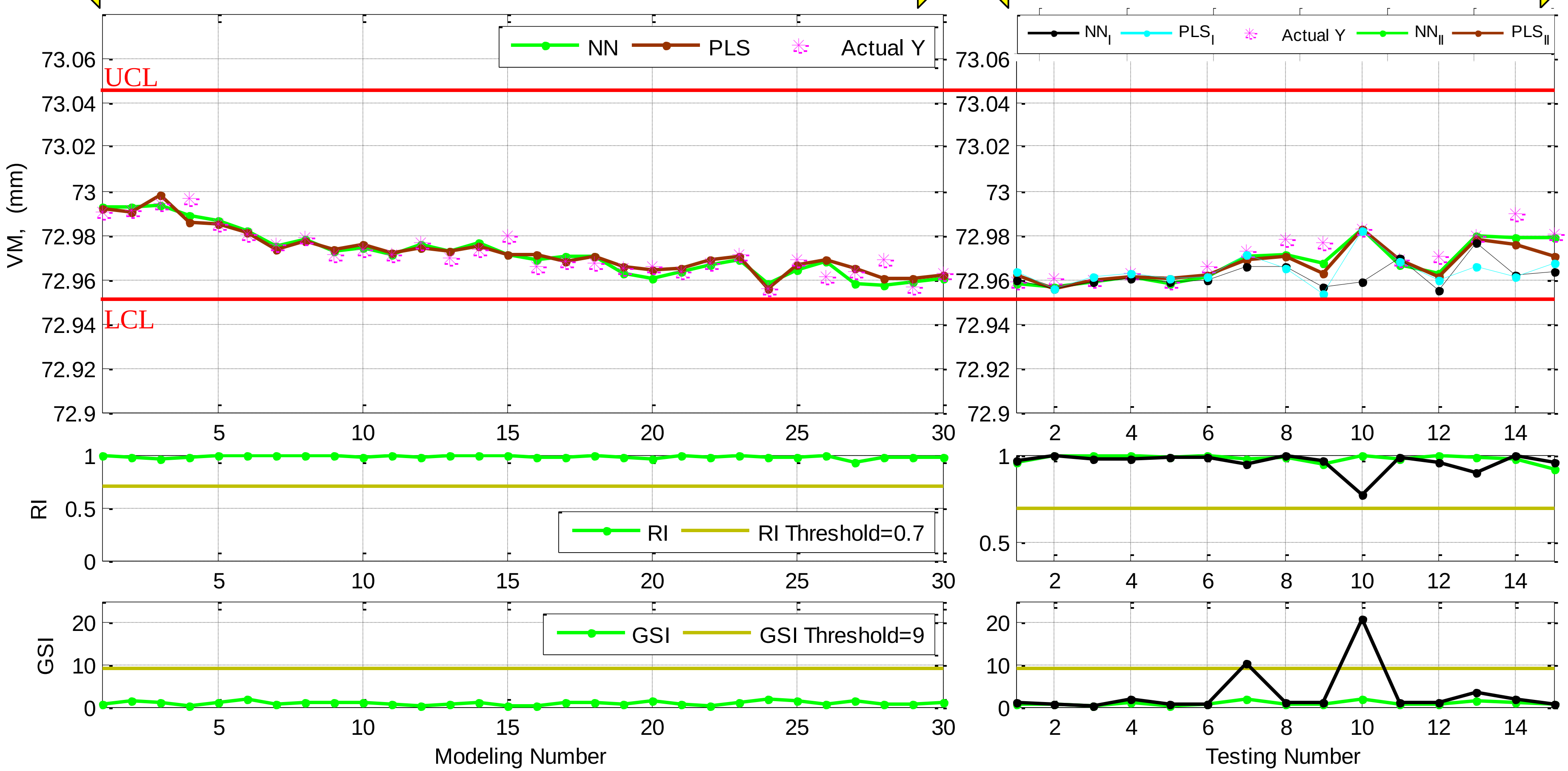
$$\#MAPE = \frac{1}{N}\sum_{n=1}^{N}\frac{(|Ypre_n - Yreal_n|)}{tolerance}$$

$$\#MAE = \frac{1}{N}\sum_{n=1}^{N}(|Ypre_n - Yreal_n|)$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|),\ n=1\ldots N$$

$$\#Max\ Error = Max(|Ypre_n - Yreal_n|/tolerance),\ n=1\ldots N$$

Modeling Samples **Testing Samples**



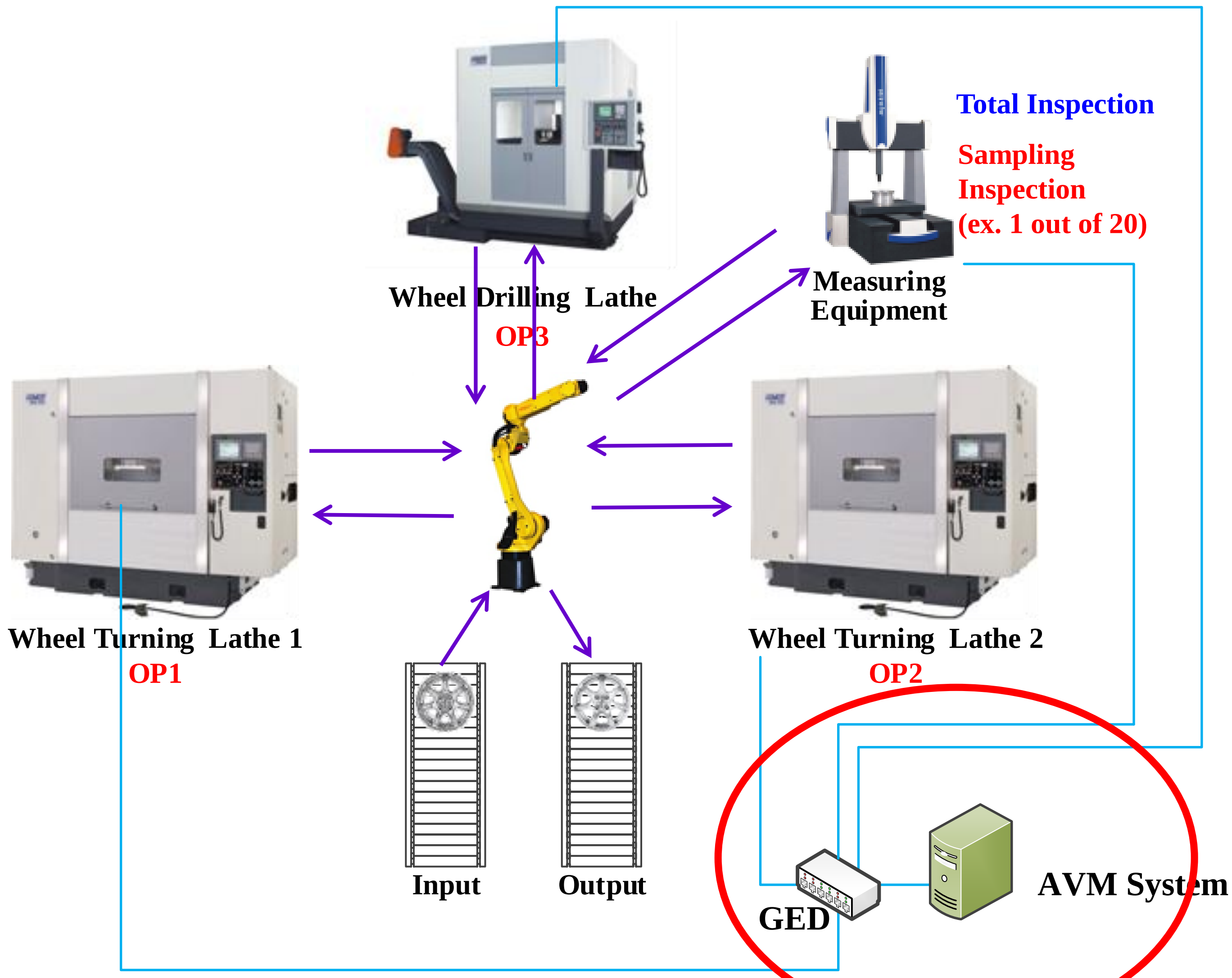
Benefits of AVM-based PPP Service

- Reduce capital expenditure of measurement tools
- Reduce cycle time of products
- Achieve workpiece-to-workpiece monitoring of product quality, i.e. total inspection
- Support baseline predictive maintenance (BPM)

Integrating AVM into Wheel Machining Automation -

Automated Production Line 2

Integrating AVM into Wheel Machining Automation – Automated Production Line 2



Demo for Integrating AVM into Wheel Machining Automation -

Automated Production Line 2

Thank You!

Q & A